P086: CORROSION ASSESSMENTS OF SOME BURIED METAL PIPES USING NEURAL NETWORK ALGORITHM

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Abstract

The key aim of this assessment is to characterize the rate of corrosion of buried Nickel Plated and non-plated AISI 1015 steel pipes using a modified Artificial Neural Network on MATLAB and taking the oil and gas area of Nigeria as a case study. 10 metal specimens were used of which 5 were nickel electroplated specimens buried differently into 5 different plastics containing soil samples and the other 5 non-plated specimens also buried into the same 5 soil samples but different plastic containers. In carrying out the experiment, the data that was collected for 25 consecutive days were grouped into sets of input and output data. This is required so as to appropriately feed the modelling tool (Artificial Neural Network). The input data are; Temperature of the soil sample, Temperature of the immediate surroundings, pH of the soil sample and with the output data to be weight loss. Conclusively, Modified Artificial Neural Network relationships between the varied selected input parameters that affects corrosion rate (soil sample temperature, immediate environment temperature and pH value) and the output parameter (Corrosion Penetration Rate) were derived.

Keywords: Corrosion, MANN, Steel Pipe, Nickel Plated and weight loss

INTRODUCTION

Oparaodu et. al in 2014 defined corrosion as the deterioration of metal or other materials brought about by chemical, mechanical and biological action by soil environment. It may be caused by chemical reactions with carbonic acid, sulphuric acid or oxygen or by electrochemical metal ion transport. This definition of corrosion given above submits that by virtue of exposure of metals to the environment, corrosion is inevitable knowing fully well that exposed Iron materials and its popular alloy, Steel suffers the most. Emami in 2012, concludes that the annual cost of corrosion worldwide is over 3% of the world's GDP. Even with this drawback, carbon steels have been on a wide application throughout the world. There are hundreds of thousands of kilometres of pipelines in various sectors of industry which include many uncoated pipelines in chemical manufacturing plants, interstate natural gas transmission lines, and offshore oil-and-gas production pipelines (Emami 2011).

According to Oyewole (2011), the high demand for oil and gas is still on the increase and pipes mostly made of carbon steel are recognized as the safest and most efficient way of transporting this product. With this fact, corrosion still remains a major problem in the transportation of oil and gas from where they are produced to where they are needed of which, pipelines buried beneath the earth are more prone to external degradation since the condition for corrosion to have effects on them are always present. These conditions are the presence of chemical substances such as Chloride, Oxygen (O_2), carbon dioxide (CO_2) hydrogen sulphide (H_2S), water. Microbiological bacteria could also cause severe corrosion problems depending on the pH values, temperature, pressure, materials flow rate and flow profile of the system (Oyewole 2011). The consequences of this unwarranted natural phenomenon ranges from financial losses causing plant shut down, lost production, product loss, product contamination, fire accidents to loss of customer confidence and

environmental degradation. Ekott et. al. in 2012 researched on external cathodic protection and control of the amount of H_2S in the buried steel oil pipelines in Niger Delta to alleviate the effect of external corrosion but this was able to effectively tackle the effect of external corrosion on this pipes, hence the need to revise this unworthy challenge.
Artificial Neural Networks models have in general good performance even if one or more input parameters are unavailable. Lee and Kim (2009) have been capable of expressing a variety of non-linear surfaces using a number of input-output training patterns that are selected from the entire design space in a global manner. It gives us understanding into many real life processes and the interplay between or among variable(s) quantifying such models.
With all these argument, MATLAB with no doubt has placed at least a little confidence on researchers on the viability of employing Artificial Neural Network models in executing there modelling related studies and has instilled a hope in this study for comprehensive modeling and analysis which is why it has been principal used in this research work to carry out an comprehensive assessment.

METHODS AND MATERIALS

This Methodology study followed the use of weight loss analysis for the determination of corrosion penetration rate. However, Modified Artificial Neural Network (MANN) was afterwards used in clarifying the pattern of the corrosion effect together with the interpretation of the derived process algorithm for the analysis.

The major materials used are:

i. AISI 1015 steel pipe
    a) Nickel-plated
    b) Non-electroplated

ii. Soil samples

The soil samples were obtained from Pan-Ocean Corporation, Ovade Ogharefe, Delta state. It is an on-shore petroleum exploration and exploration site.

a) Tank farm
b) Skimmer pit
c) Export pump
d) Saver Pit
e) Arrival manifold point

iii. Crude oil

This was gotten from the Shell Petroleum Development Company, North bank flow station, Obotobol, Forcados, Delta state.

The experiment procedure

Ten metal specimens were used. 5 were nickel electroplated specimens buried differently into the 5 different plastics containing soil samples with the other 5 non-plated specimens also buried into the same 5 soil samples but different plastic containers. In carrying out the experiment, the data were grouped into sets of input and output data. This is required so as to appropriately feed the modelling tool (Artificial Neural Network). The input data are:

- Temperature of the soil sample
- Temperature of the immediate surrounding
- pH of the soil sample

With the output data to be:

- weight loss

Soil samples temperatures

This is the temperature of the soil samples having the steel specimens buried in them. The activity was carried out at the burial site with a laboratory thermometer of calibration -10 ^{o}C to 110 ^{o}C. This was to allow for actual temperature of the set-up affected by the corrosion as temperature change affects the rate of corrosion of a substance.

Immediate surroundings temperatures

This is the temperature of the immediate surroundings of the whole set-up. For a better and more precise modelling, this parameter was recorded. Also, a laboratory thermometer of calibration -10 ^{o}C to 110 ^{o}C was used and it was carried out on-site.

pH values

From the reviewed literatures it was ascertained that the rate of corrosion is largely affected by the change in the pH values. This therefore made it highly required for it to be recorded from the experiment. Hanna brand pH metre of accuracy 0.1 was use. And the activity was carried out on site. At the first day, the pH meter was calibrated with a buffer solution of pH 4.0 then at the fourth day with a buffer solution of pH 10.0. This was necessary so as to allow for maximum accuracy of the pH metre. After taking all the pH readings, the soil minimum pH values for the non-electroplated and the electroplated specimens were 6.9 and 6.8 respectively while the maximum were 8.3 and 8.4. This conforms to the works of Oyewole (2011).

The figure below shows the pH reading been collected at the soil sample 5 for the nickel-electroplated steel material with the digital pH meter.

Figure 2: Shows taking of pH reading for Soil sample E, nickel-electroplated

Figure 3: Picture of the non-electroplated steel specimen

Figure 4: Picture of the nickel-electroplated steel specimen

RESULT AND DISCUSSION

Analysis using Modified Artificial Neural Network (MANN)

A function of MATLAB is ANN. As postulated by (Lee and Kim 2009), ANN is one of the most efficient ways of solving complex problems bit by bit. Also, as posited by (Lee and Kim, 2009), ANNs have the capacity to handle variety of non-linear surfaces using a number of input and output training patterns selected from the entire total field of possible data.

It was used in this study as a modelling tool on a series of seemingly unrelated input and output data collected to;

i. Train a pattern for the corrosion penetration rate
ii. Investigate the effect of the input data in contribution to the corrosion penetration rate
iii. Predict for outlying data accurately when computing in real life situations
iv. Generate algorithms which could be used propose for possible results of the output (corrosion penetration rate) in the future when input data are varied
v. Plot graphs in various formats by manipulating data and executing simples codes

Training of the Modified Artificial Neural Network

The first task carried out on the modelling tool was training. Training in Artificial Neural Network is the process of exercising the modelling tool in order to allow it learns a particular pattern of behaviour before using it. The larger the number of data used for the training process, the more efficient and reliable the tool. This permits the tool to be able to handle a wide range of stochastic input data parameter efficiently. For this study, the whole 125 data collected for the 25 days was used for training the software.

Encoding in the Modified Artificial Neural Networks

As earlier stated in the previous chapter, the network requires input and output data. The input data are the data recorded which contribute to the corrosion penetration rate of the buried specimens while the output data is the data recorded which results from the effect of the various input parameters. The input data recorded are:

i. Soil sample temperature
ii. Immediate surrounding temperature
iii. pH value

While the output data recorded is:

i. Weight loss

The weight loss data recorded was afterwards translated to corrosion penetration rate. This was achieved by using the formula below as postulated by Emami (2011):

$$\mathrm{CPR} = \frac{87.6 \text{ x } \mathrm{W}}{\mathrm{D} \text{ x } \mathrm{A} \text{ x } \mathrm{T}} \qquad (\mathrm{mm/y})$$

Where:

CPR: Corrosion penetration rate in (mm/y)
W: Weight of the buried material at instances in (g)
D: Density of the buried material in (g/cm^3)

T: Time in (hrs)

In computing the various CPR(s) for the corresponding weight loss values, Microsoft excel was used extensively. The results displayed on the Microsoft excel were imported to the Matlab environment for further MANN analysis. This is due to the compatibility between the two computer softwares. The figure below shows the various input and output for the neural network.

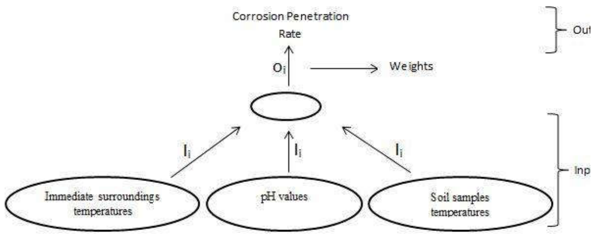

Figure 5: Input and output for the neural network

Dealing with neural networks, there are various encoding format. But for this study, the codes were developed newly. For this reason, the neural networks become modified thereby allowing for introduction of polynomial approximation (list square) format instead of the default neurons. The figure below shows the flow chart for the MANN.

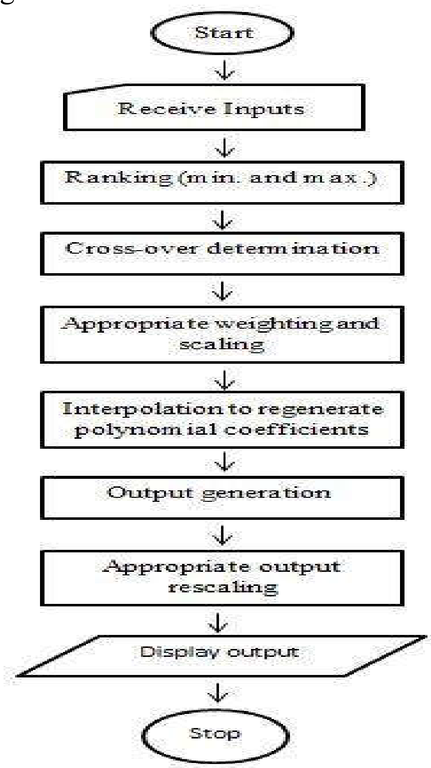

Figure 6: Flow chart for the Modified Artificial Neural Network

While modelling on the experiment on the MANN, four cases where considered. The cases are:

i. All the three inputs
ii. The first two inputs only
iii. The first and the last inputs only
iv. The last two inputs only

Following the flow chart on figure 12 above, a sequential overview of the algorithm is however presented:

1. Start: This is a compilation initiation command.

2. Receive inputs: The input data received as been read from the Microsoft excel file saved in Matlab default folder are extracted into the Matlab memory.
3. Ranking: This is more of sorting out of the data. The first input which was the soil sample temperature was ranked. In respect of this, corresponding changes was applied across other input parameters which are immediate surroundings temperature and pH values and the output parameters.
4. Cross-over determination: This is the estimation of the number of turning points present in the output (corrosion penetration rate). For this analysis, the turning points were constrained to 2. This gave rise to a cubic polynomial equation (i.e. order 3). In the data used there are more than 2 turning points with the changes in the values not critically high. From this, a line of best fit was drawn while approximating by the lead square.
5. Appropriate weighting and scaling: Scaling was introduced so as to allow for convergence of all the data. This harmonises them to an approximately the same decimal fraction so they can relate well. This is appropriate because of the extreme nature of the values. Weighting on the other side tells the degree of contribution of an input over the other. But since the degree of contribution of the inputs had not been certified, they were all assumed to have the same relevance.
6. Interpolation to regenerate polynomial coefficient: This is the application of list square to establish a polynomial expression that generates a relationship between the CPR and all the inputs under consideration.
7. Output generation: The output computed.
8. Appropriate output rescaling: This recalled the scaling magnitude used earlier in step 5 and adjusted the output before displaying.
9. Stop: The computation ends

The transitions obtained from the output matrix are thus used in generating the order of the polynomial function. The first output is given as $\mathbf{K(I) = aI^2 + bI + c}$. The second input is modelled similarly which are used in generating the respective values of **a1**, **b1** and **c1**. The second output is thus given as $\mathbf{K(J) = a1J^2 + b1J + c1}$. The final output is therefore the average of this two values given as: $\mathbf{K = (K(I) + K(J)) / 2}$.

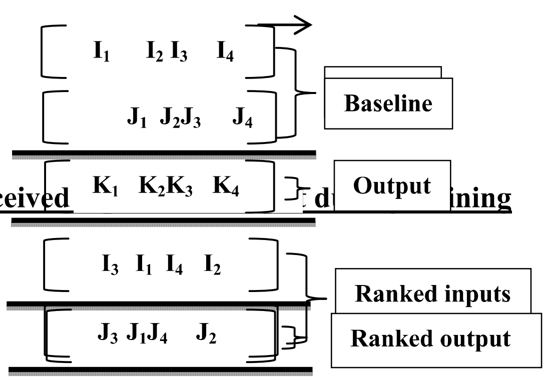

Fig a: received d ining

Fig b: ranked received inputs and output using baseline

If

$$\left.\begin{array}{l} K_1 > K_3 \\ K_1 > K_4 \\ K_2 < K_4 \end{array}\right\} \ldots \text{(a)}$$

Where I_i, J_i and K_i ($i = 1, 2, 3, 4$) are valid inputs and output respectively, then the number of cross overs could be determined from the ranked output

Two cross over signifies that the data could be modelled using a polynomial of order 3 (i.e. a cubic equation). In modelling therefore, the following equations are used:

$$\sum K_i = a*n + b\sum_{i=1}^{n} I_i + c\sum_{i=1}^{n} I_i^2 \quad \text{... (b)}$$

$$\sum K_i I_i = a\sum_{i=1}^{n} I_i + b\sum_{i=1}^{n} I_i^2 + c\sum_{i=1}^{n} I_i^3 \quad \text{... (c)}$$

$$\sum K_i I_i^2 = a\sum_{i=1}^{n} I_i^2 + b\sum_{i=1}^{n} I_i^3 + c\sum_{i=1}^{n} I_i^4 \quad \text{... (d)}$$

$$\sum K_i = a1*n + b1\sum_{i=1}^{n} J_i + c1\sum_{i=1}^{n} J_i^2 \quad \text{... (e)}$$

$$\sum K_i J_i = a1\sum_{i=1}^{n} J_i + b1\sum_{i=1}^{n} J_i^2 + c1\sum_{i=1}^{n} J_i^3 \quad \text{... (f)}$$

$$\sum K_i J_i^2 = a1\sum_{i=1}^{n} J_i^2 + b1\sum_{i=1}^{n} J_i^3 + c1\sum_{i=1}^{n} J_i^4 \quad \text{... (g)}$$

CASE 1

The corrosion penetration rate is determined by all the three contributing factors, the soil temperatures, the immediate surroundings temperatures and the pH values. These factors are appropriately scaled and uniformly (unity) weighted. The validity of this case scenarios would be based on its deviation from the standard calculated CPR.

In modelling the corrosion penetration rate under this case scenario, the following parameters are defined;

Let k be the number of inputs being considered

$k = 3$ … (1)

Highest order of polynomial, n, being considered is 3 … (2)

Let W_i be the respective weights for the inputs (soil temperatures, immediate surrounding temperatures and pH values)

Let Sf_i be the respective scaling factor for each input considered

$$CPR = 0.33 * \sum_{i=1}^{k} (a_i + b_i*x_i + c_i*x_i^2 + d_i*x_i^3) \quad \text{… (3)}$$

Where a_i, b_i, c_i and d_i are the respective constants for each respective input

$b_i = b * Sf_i * W_i$ … (4)

$c_i = c * Sf_i * W_i$ … (5)

$d_i = d * Sf_i * W_i$ … (6)

CASE 2

The corrosion penetration rate is determined by the first two contributing factors only, the soil temperatures and the immediate surroundings temperatures. These factors are appropriately scaled and uniformly (unity) weighted. The validity of this case scenarios would be based on its deviation from the standard calculated CPR.

In modelling the corrosion penetration rate under this case scenario, the following parameters are defined;

Let k be the number of inputs being considered

$k = 2$ … (7)

Highest order of polynomial, n, being considered is 3 … (8)

Let W_i be the respective weights for the inputs (soil temperatures and immediate surrounding temperatures)

Let Sf_i be the respective scaling factor for each input considered

$$CPR = 0.50 * \sum_{i=1}^{k} (a_i + b_i*x_i + c_i*x_i^2 + d_i*x_i^3) \quad \text{… (9)}$$

Where a_i, b_i, c_i and d_i are the respective constants for each respective input

$b_i = b * Sf_i * W_i$ …(10)

$c_i = c * Sf_i * W_i$ … (11)

$d_i = d * Sf_i * W_i$ … (12)

CASE 3

The corrosion penetration rate is determined by the first and the last contributing factors only, the soil temperatures and the pH values. These factors are appropriately scaled and uniformly (unity) weighted. The validity of this case scenarios would be based on its deviation from the standard calculated CPR.

In modelling the corrosion penetration rate under this case scenario, the following parameters are defined;

Let k be the number of inputs being considered

$k = 2$ … (13)

Highest order of polynomial, n, being considered is 3 … (14)

Let W_i be the respective weights for the inputs (soil temperatures and immediate surrounding temperatures)

Let Sf_i be the respective scaling factor for each input considered

$$CPR = 0.50 * \sum_{i=1}^{K=2} (a_i + b_i*x_i + c_i*x_i^2 + d_i*x_i^3) \quad \text{… (15)}$$

Where a_i, b_i, c_i and d_i are the respective constants for each respective input

$b_i = b * Sf_i * W_i$ … (16)

$c_i = c * Sf_i * W_i$ … (17)

$d_i = d * Sf_i * W_i$ … (18)

CASE 4

The corrosion penetration rate is determined by the last two contributing factors, the immediate surroundings temperatures and the pH values. These factors are appropriately scaled and uniformly (unity) weighted. The validity of this case scenarios would be based on its deviation from the standard calculated CPR.

In modelling the corrosion penetration rate under this case scenario, the following parameters are defined;

Let k be the number of inputs being considered

$k = 2$ … (19)

Highest order of polynomial, n, being considered is 3 … (20)

Let W_i be the respective weights for the inputs (soil temperatures and immediate surrounding temperatures)

Let Sf_i be the respective scaling factor for each input considered

$$CPR = 0.50 * \sum_{i=1}^{k} (a_i + b_i * x_i + c_i * x_i^2 + d_i * x_i^3) \quad \ldots (21)$$

Where a_i, b_i, c_i and d_i are the respective constants for each respective input

$$b_i = b * Sf_i * W_i \quad \ldots (22)$$

$$c_i = c * Sf_i * W_i \quad \ldots (23)$$

$$d_i = d * Sf_i * W_i \quad \ldots (24)$$

The scaling factors are therefore;

Sf = 0.1 soil sample temperature … (25)

Sf = 0.1 immediate surrounding temperature … (26)

Sf = 1 pH value … (27)

Sf = 1000 corrosion penetration rate … (28)

Obervation:

However, the numerical differences between the CPR values of the electroplated and the non-electroplated specimens are somewhat small.

The graphical representations of the modified artificial neural network are presented below:

Graphical representation of the modified artificial neural network results

Modified Artificial Neural Network was more extensively used for the analysis therefore; more interpretations were deduced from the generated graphical results as further explained below. On each graph generated, there are five continuous lines having different colours. Each coloured line is interpreted as below:

i. Blue line: Plot for all the three input parameters that influenced the output parameter as measured
ii. Green line: Plot for all the three input parameters that influenced the output as modelled by the software
iii. Red line Plot for the first two inputs as modelled by the software
iv. Cyan line: Plot for the first and the last input as modelled by the software
v. Purple line: Plot for the last two input as modelled by the software

The blue line which plots for the measured parameters serves as the reference for other plots. Other plots are modelled plots by the modified artificial neural networks.

The graphs below show the MANN results for the non-electroplated and the electroplated specimens in sample 1. The plots for the four cases are distant from the measured (reference) plot (blue line). This is due to a variation in training the tool.

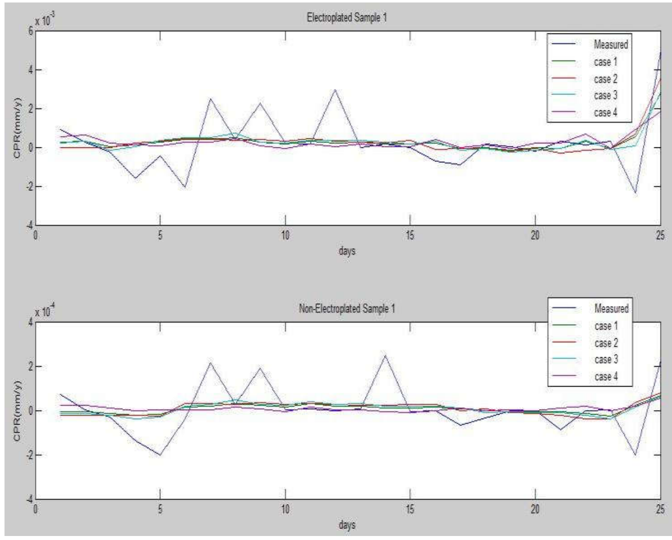

Figure 7: ANN graphical result for soil sample 1 (electroplated and non-electroplated)

The graphs below show the MANN results for the non-electroplated and the electroplated specimens in sample 2. The plots for the four cases too are distant from the measured (reference) plot (blue line). This is also due to a variation in training the tool.

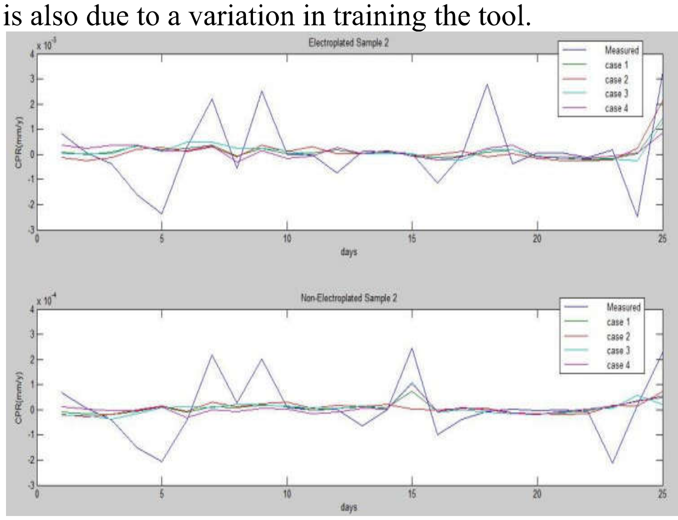

Figure 8: ANN graphical result for soil sample 2 (electroplated and non-electroplated)

Here, the graphs show the MANN results for the non-electroplated and the electroplated specimens in sample 3 to match well except for variations in days 13 and 15 in the case of the electroplated specimen and only day 17 in the case of the non-electroplated specimen. This is due to a variation in training the tool.

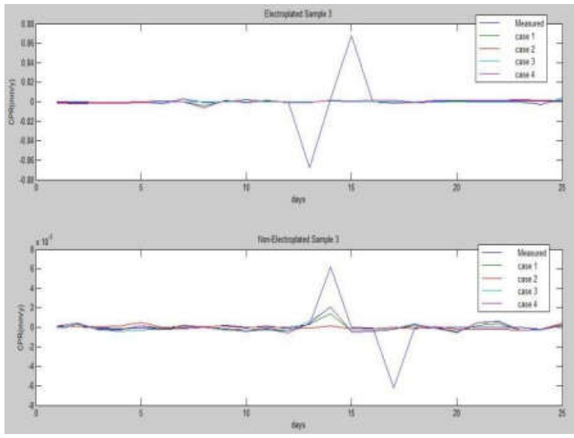

Figure 9: ANN graphical result for soil sample 4 (electroplated and non-electroplated)

Unlike the earlier plotted graphs, the electroplated graph for the sample 3 matches so well that there were only two outlying data at days 1 and 2 whereas for the non-electroplated specimen, did not really conform but conforms between days 9 and 13, days19 and 23 and day 25.

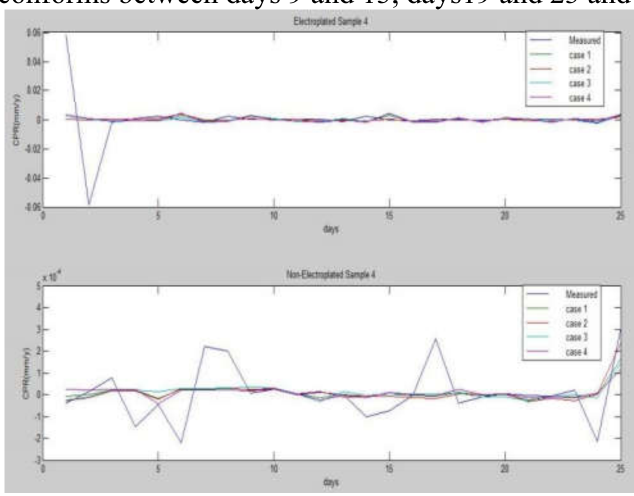

Figure 10: ANN graphical result for soil sample 4 (electroplated and non-electroplated)

The results for specimens in sample 5 have two variations in their measured plot. For the electroplated specimen, the variations are at days 7 and 12 while for the non-electroplated specimen, the variations are on days 8 and 14.

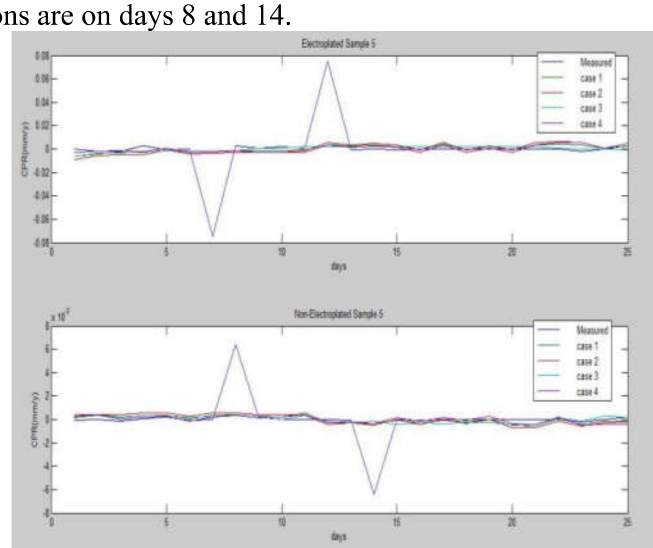

Figure 11: ANN graphical result for soil sample 5 (electroplated and non-electroplated)

Determination of the relevance of each case was done by using the percentage error method on the modified artificial neutral network:

The results from the modified artificial neural network also include the percentage error of each case. This is presented below:

Percentage errors
case 1: -4.0410e-013
case 2: -6.0080e-013
case 3: -4.3490e-013
case 4: -1.7660e-013

From the above results, it is therefore deduced that;

- Case 2: Soil sample temperature and the immediate surrounding temperature (has the strongest effect on the corrosion penetration rate).
- Case 3: Soil sample temperature and the pH
- Case 1: The soil sample temperature, immediate surrounding temperature and the pH value)
- Case 4: Immediate temperature and the pH value (has the weakest effect on the corrosion penetration rate).

The cases above are arranged in the order of relevance on the corrosion penetration rate.

ANN graphical result for soil sample 5 (electroplated and non-electroplated)

CONCLUSION

Modified Artificial Neural Network relationships between the varied selected input parameters that affects corrosion rate (soil sample temperature, immediate environment temperature and pH value) and the output parameter (Corrosion Penetration Rate) were derived.

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